# ViTopic – Topic Modeling on Images by Clustering of Vision Transformer Embeddings

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Project Homepage: https://github.com/faustotnc/vitopic/

# Problem Statement & Motivation

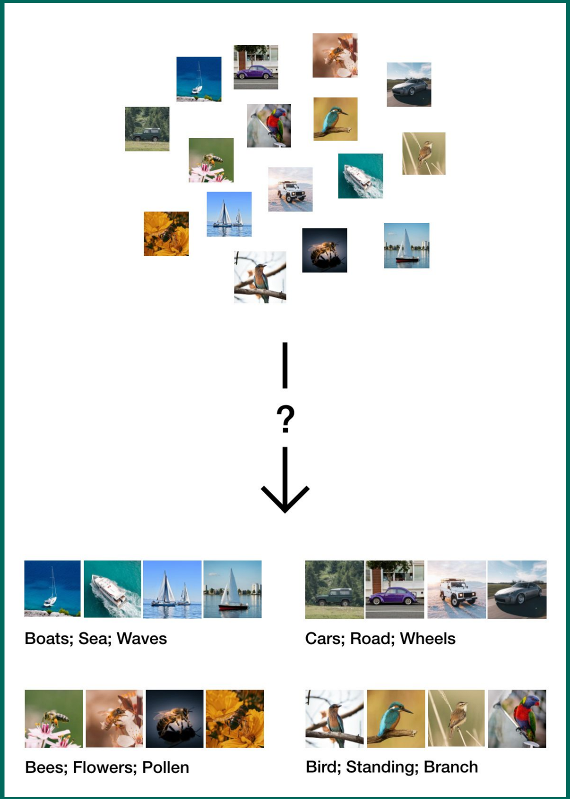
- Image data plays an important role in fields like social media analysis, medical research, and agriculture.
- Collecting, sorting, and clustering image data are resource-intensive tasks.
- Human intervention is still need to interpret the contents of groups of images.

## Problem Statement

- How do we cluster a collection of unlabeled images and generate topic descriptors based on their visual context?

## Why is this important?

- Automating every step of the process could drastically decrease labor costs and make analysing image data more accessible.




* Images from Unsplash

# Related Work

**Title**: Contextual Visual Similarity

**Authors**: Xiaofang Wang, Kris M. Kitani and Martial Hebert

**Year**: 2016

**Publisher**: ArXiv

**URL**: https://arxiv.org/abs/1612.02534

# Related Work

In their research the authors use triples of images for unsupervised attribute discovery, where they learn feature weights for each triplet such that the distance between two triplets is small if they are similar.

The main difference between their method and the methods I plan to use is that they require three images (A query image, a positive example, and a negative example) to define a contextualized similarity search criterion, while ViTopic computes similarity based on the Inverse Euclidean Distance between Vision Transformer Embeddings.

# Other Related Work

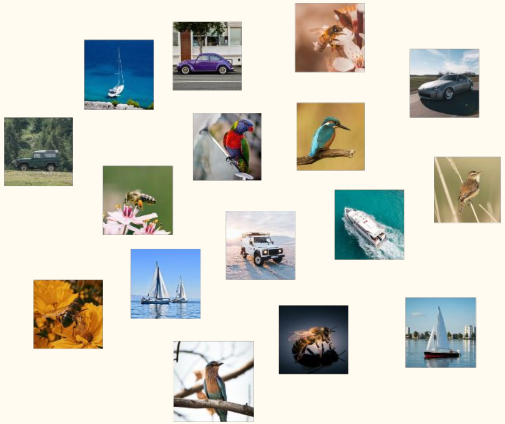
This project combines the work from recent research on computer vision models and topic modeling techniques:

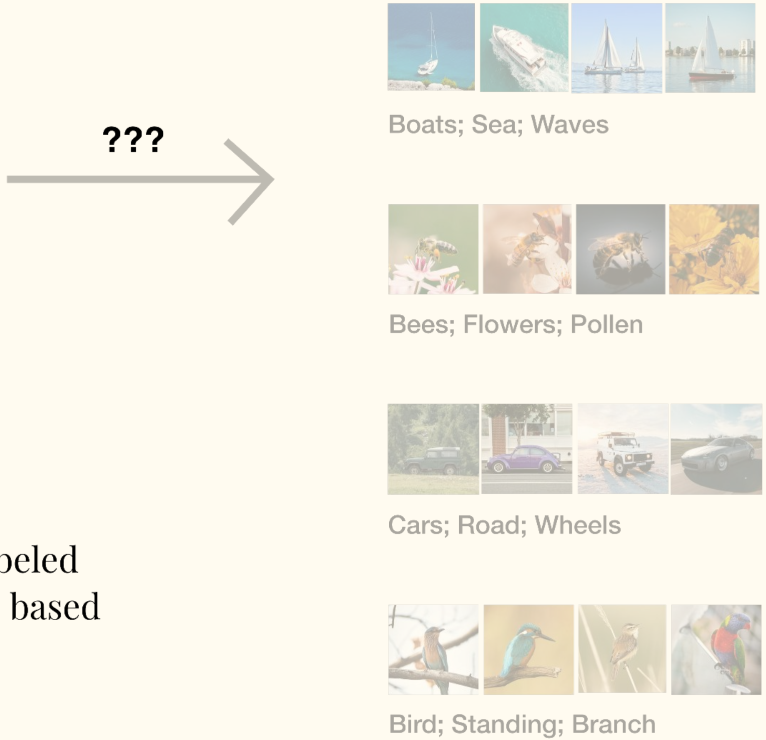
1. **Swin Transformer: Hierarchical vision transformer using shifted windows.**
   a. By Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Published to ArXiv on August 17, 2021.
   b. **Why this paper?** It describes Vision Transformers, which I plan to use to compute image embeddings for contextual similarity.

2. **Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation**
   a. By Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. Published to ArXiv on February 15, 2022.
   b. **Why this paper?** It describes the model I plan to use for automated image-captioning.

3. **BERTopic: Neural topic modeling with a class-based TF-IDF procedure.**
   a. By Maarten Grootendorst. Published to ArXiv on March 11, 2022.
   b. **Why this paper?** It describes the pipeline I plan to use to create contextual topics.

# Main Idea – Visually Explained

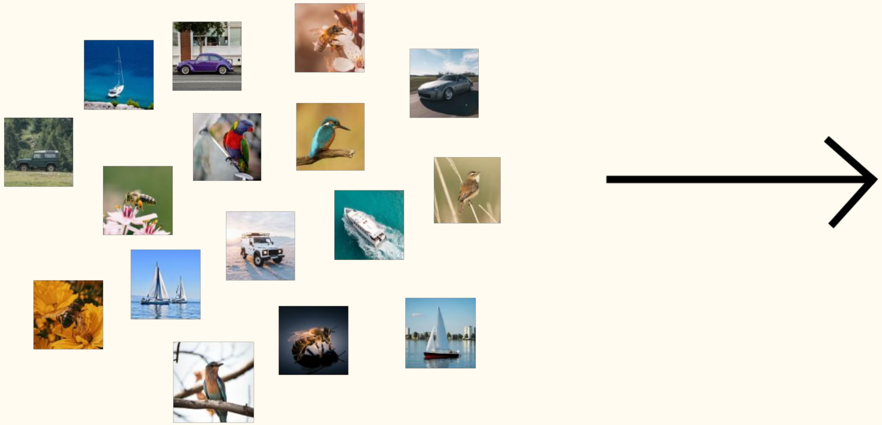


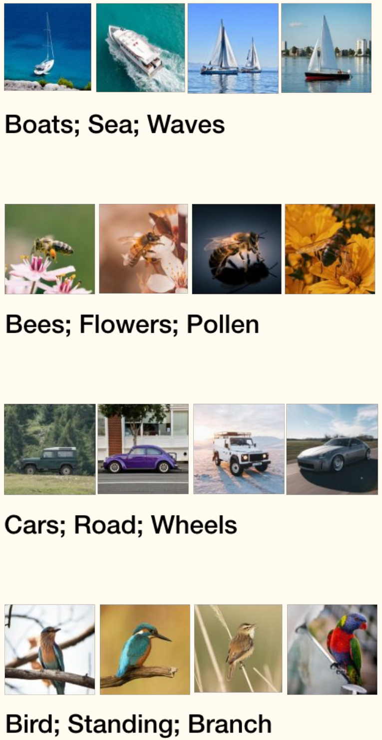



How do we cluster a collection of unlabeled images and generate topic descriptors based on their visual context?

* Images from Unsplash

# Main Idea – Visually Explained






Each image is assigned a cluster (as determined by their transformer embeddings). Then, each image is described using an image captioning model, and topic descriptors are generated based on the frequency of words in the captions.

* Images from Unsplash

# The Data

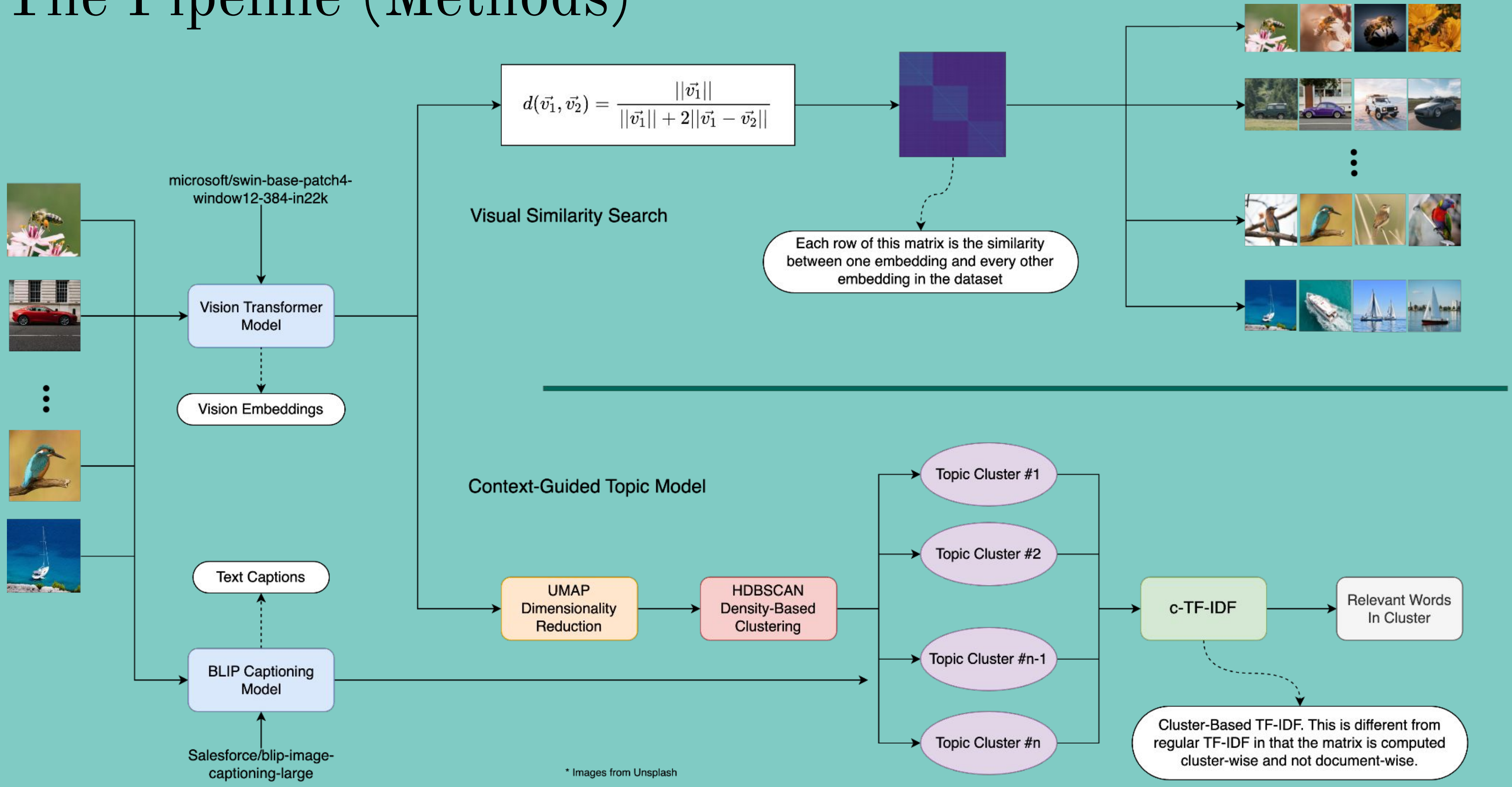
I will use the ImageNette dataset, which is a small subset of the ImageNet project.

We can easily access this subset using the Datasets library from the HuggingFace repository: https://huggingface.co/datasets/frgfm/imagenette

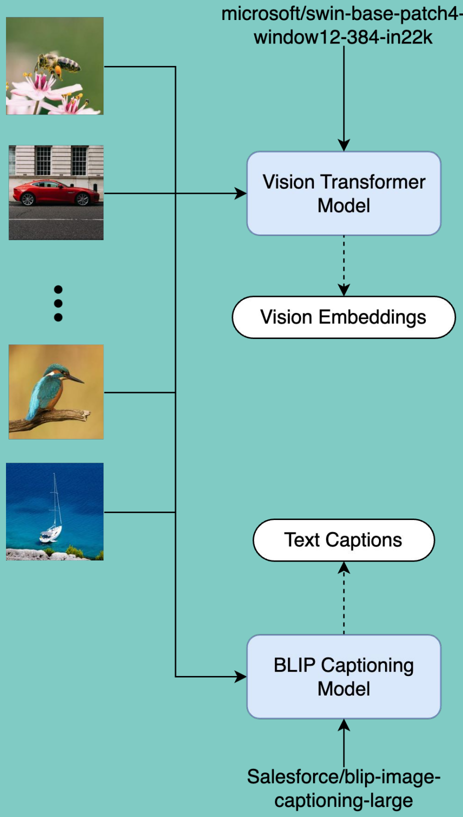
This dataset will make it possible to evaluate the performance of the system since it contains labeled images within a small number of classes.

https://paperswithcode.com/dataset/imagenet

# The Pipeline (Methods)

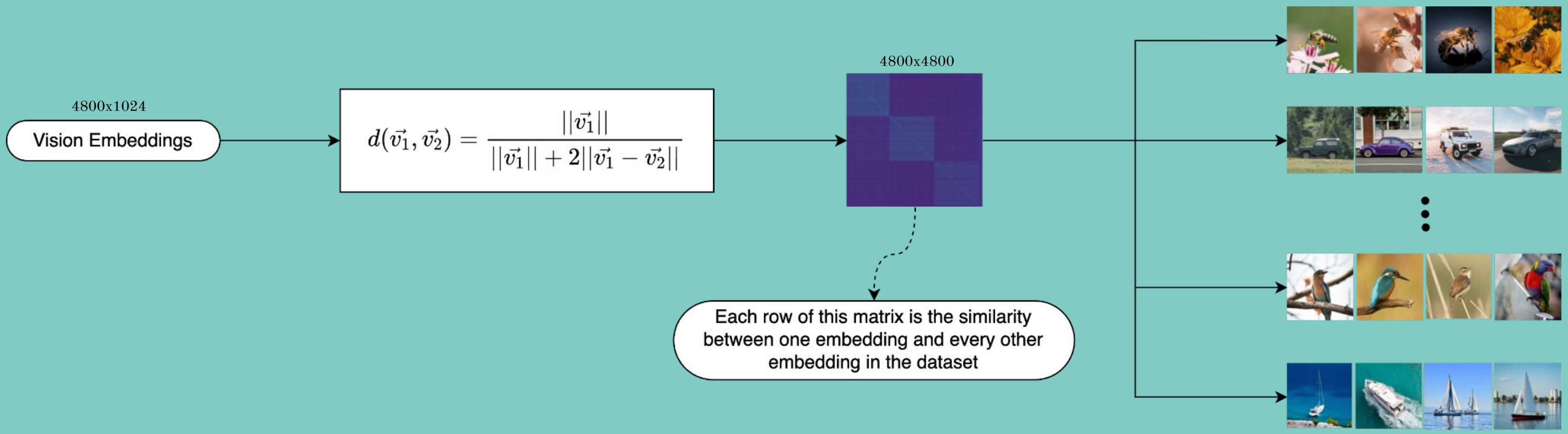


# The Pipeline (Methods) – Embeddings & Captions



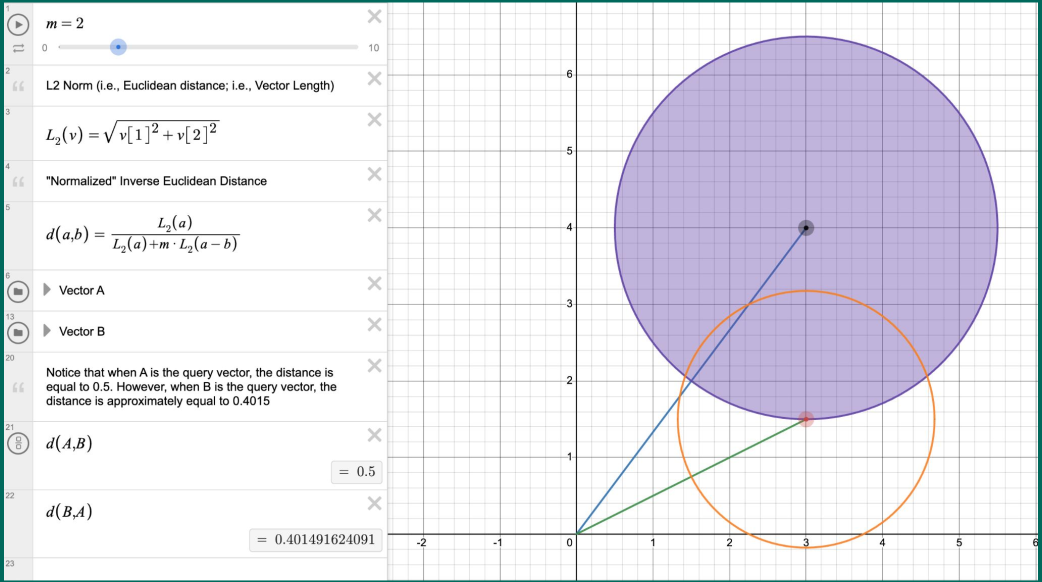

- Take the images and generate vision embeddings and captions
- SWIN Transformer Model for Vision Embeddings
- BLIP Model for Image Captioning

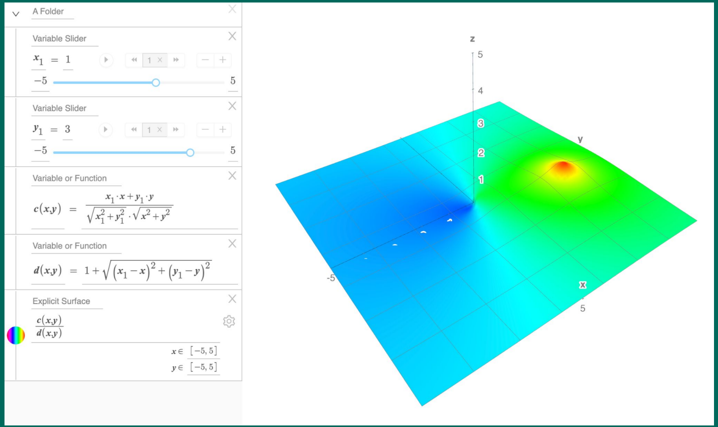
# The Pipeline (Methods) – Visual Similarity Search




- Generate similarity matrix from vision embeddings
- Use Inverse Euclidean distance to compute similarity scores
- Sort entries by value

# Side Note – Similarity Function & Variations



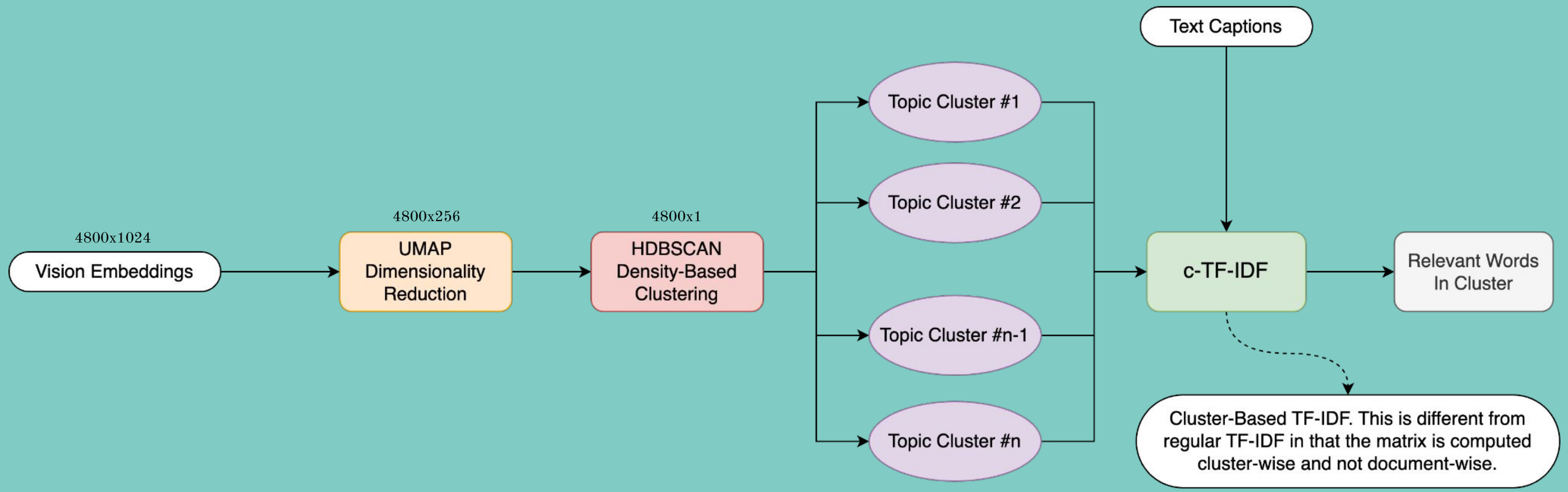

- "Query-Scaled" inverse Euclidean distance
- Takes into account the length of each embedding vector
- Assumes that the query embedding is at the center of a perfect hypersphere

Why not Cosine Similarity?

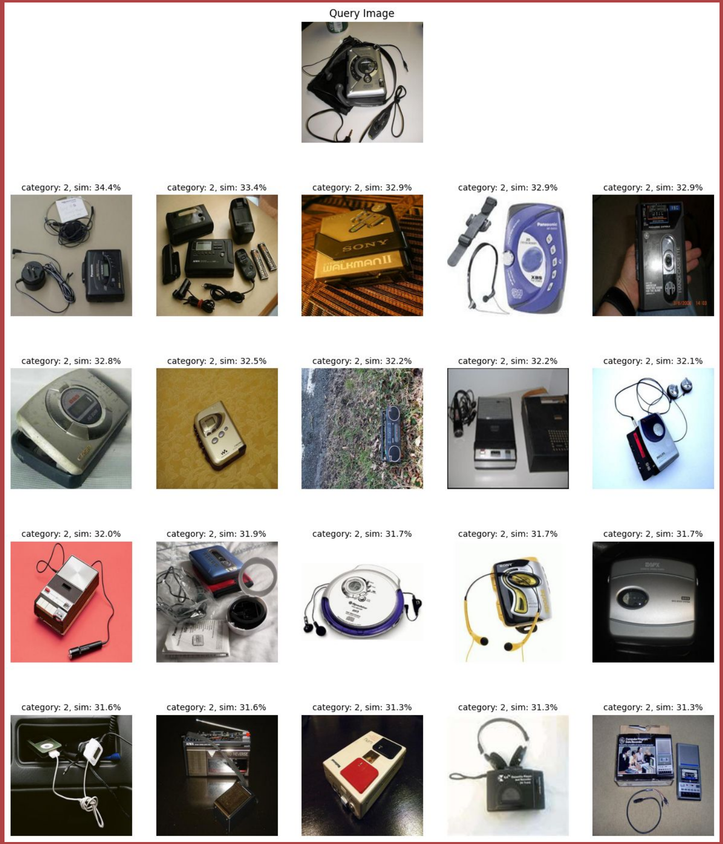
- Incorporating cosine similarity into the equation produces similar results
- Unlike text embeddings, image embeddings do not capture polarity very well

# The Pipeline (Methods) – Concept-Guided Topic Model

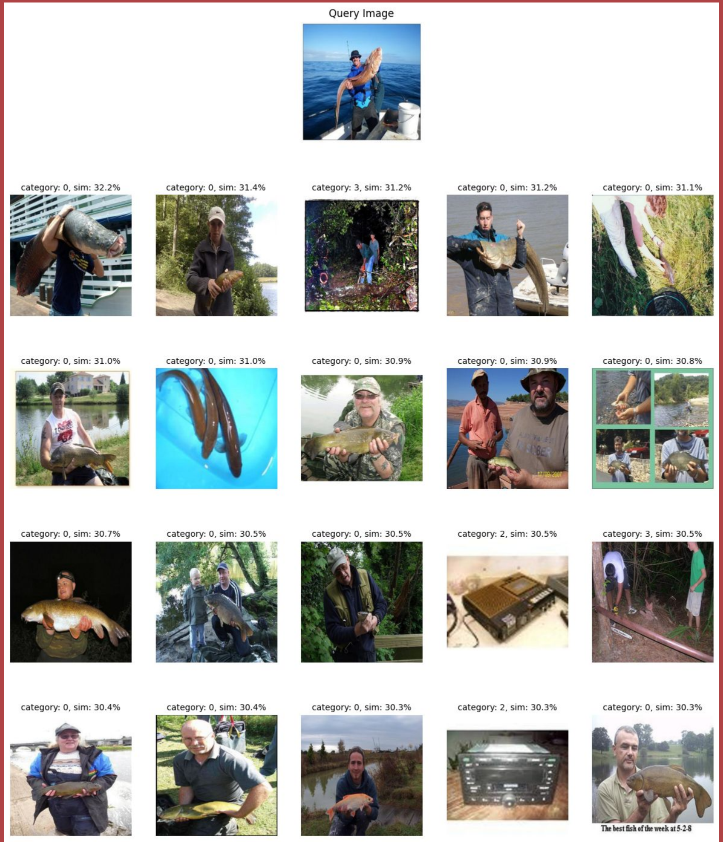
- Use vision embeddings and text captions to find topic descriptors (frequent words) guided by the conceptual information of the images
- Use UMAP & HDBSCAN for clustering of vision embeddings
- Use the text captions and cluster information for topic discovery



# Results – Visual Similarity Search

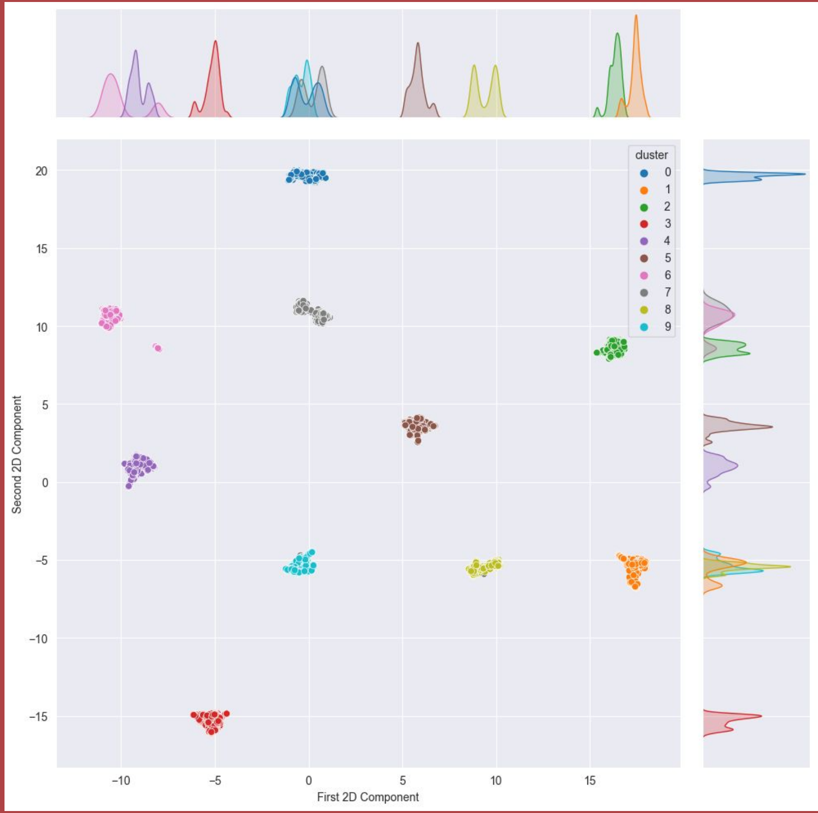



# Results – Visual Similarity Search




It's not a perfect solution.

# Results – Concept-Guided Topic Model




| | Topic #0 | | Topic #1 | | Topic #2 | | Topic #3 | |
|---|---|---|---|---|---|---|---|---|
| 1 | golf | 0.41285 | fish | 0.42141 | dog | 0.44577 | truck | 0.43295 |
| 2 | ball | 0.32763 | holding | 0.22051 | laying | 0.16123 | araf | 0.27578 |
| 3 | close | 0.18265 | man | 0.19609 | grass | 0.144 | parked | 0.21547 |
| 4 | balls | 0.17148 | caught | 0.17625 | standing | 0.1381 | garbage | 0.19853 |
| 5 | grass | 0.10705 | hands | 0.14238 | sitting | 0.12956 | road | 0.17481 |
| 6 | green | 0.10309 | kneeling | 0.13034 | dogs | 0.10371 | street | 0.17224 |
| 7 | tee | 0.08229 | araffe | 0.10046 | floor | 0.09872 | driving | 0.13885 |
| 8 | field | 0.06633 | arafed | 0.09745 | mouth | 0.09101 | lot | 0.09386 |
| 9 | club | 0.04815 | net | 0.09248 | frisbee | 0.09098 | parking | 0.08043 |
| 10 | hole | 0.04744 | river | 0.07655 | puppy | 0.08489 | standing | 0.0659 |

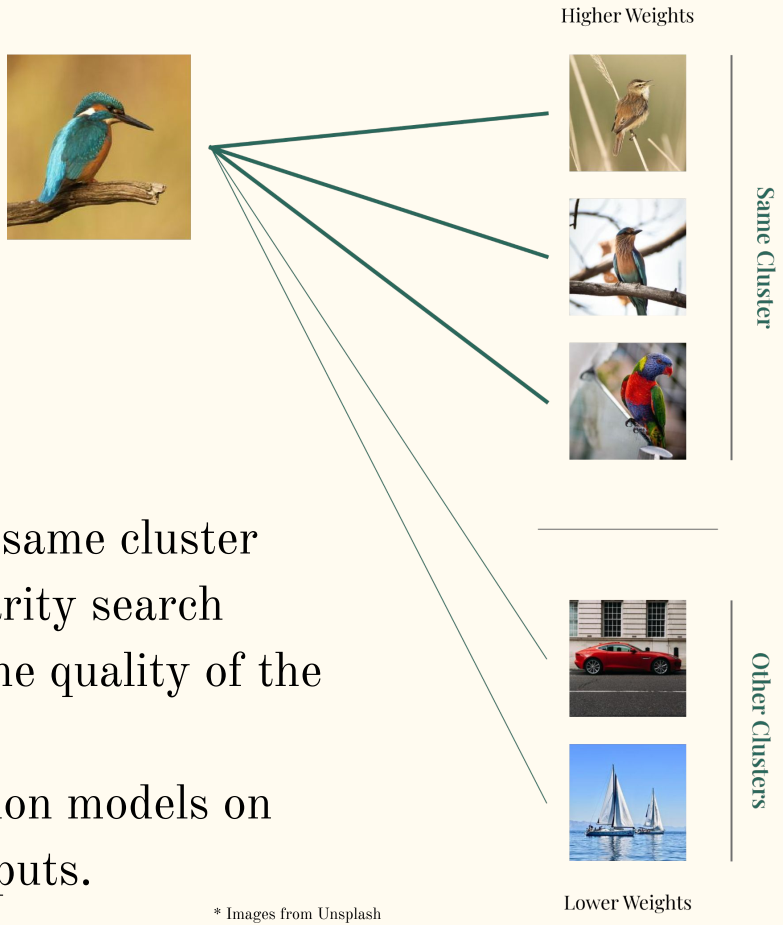
| | Topic #4 | | Topic #5 | | Topic #6 | | Topic #7 | |
|---|---|---|---|---|---|---|---|---|
| 1 | radio | 0.33948 | parachute | 0.30839 | church | 0.3368 | horn | 0.23816 |
| 2 | close | 0.20243 | flying | 0.30473 | steeple | 0.20044 | French | 0.21051 |
| 3 | player | 0.17036 | sky | 0.24832 | clock | 0.1917 | brass | 0.20206 |
| 4 | table | 0.12594 | araffe | 0.17634 | tower | 0.18597 | playing | 0.18343 |
| 5 | stereo | 0.11957 | air | 0.15293 | view | 0.17128 | instrument | 0.15722 |
| 6 | cassette | 0.11668 | person | 0.1179 | arafed | 0.16009 | instruments | 0.1059 |
| 7 | remote | 0.09721 | kite | 0.1165 | building | 0.10356 | sitting | 0.08779 |
| 8 | cd | 0.07453 | people | 0.0876 | large | 0.09353 | silver | 0.08279 |
| 9 | sitting | 0.07121 | flag | 0.0816 | cross | 0.07359 | room | 0.08119 |
| 10 | speakers | 0.06938 | parasailing | 0.0775 | white | 0.07264 | woman | 0.07964 |

| | Topic #8 | | Topic #9 | |
|---|---|---|---|---|
| 1 | chainsaw | 0.37854 | gas | 0.43259 |
| 2 | tree | 0.17521 | pump | 0.33474 |
| 3 | cutting | 0.13872 | station | 0.12938 |
| 4 | man | 0.12494 | pumps | 0.10886 |
| 5 | handle | 0.09879 | sitting | 0.10357 |
| 6 | arafed | 0.09543 | sign | 0.1013 |
| 7 | cut | 0.091 | old | 0.09499 |
| 8 | using | 0.08525 | red | 0.08703 |
| 9 | dew | 0.07936 | building | 0.076 |
| 10 | close | 0.06073 | arafed | 0.07219 |

- There is some overlap between topics #1 and #8
- This relates to the results we saw in the visual similarity search

# Conclusion & Future Work

- Using vision transformer embeddings with image captioning is a viable method for clustering images based on context topics




## Potential Improvements

- Prioritizing neighboring vectors within the same cluster could improve the result of the visual similarity search
- Using newer vision models could improve the quality of the embeddings
- Using transfer learning to fine-tune the vision models on specific tasks could greatly improve the outputs.

* Images from Unsplash

# References


- Grootendorst, M. (2022, March 11). BERTopic: *Neural topic modeling with a class-based TF-IDF procedure*. arXiv.org. Retrieved March 17, 2023, from https://arxiv.org/abs/2203.05794
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